Combining Colour Signatures

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Abstract

There are a large amount of signatures and distances within the CBIR field. All of them are only approaches that do not produce the results of high quality as desired by the user. In order to improve the quality of results, combining features seems to be a good idea. In this paper, we address the feature's combination issue based on three manners: the re-ranking mechanism is employed generally as a relevance feedback tool, the utility concept relies on the images rank and the third method is based on a mathematic formula that conjoins features. The features put under experimentation here are: histogram with 27 fixed bins, the 3 color moments: mean variance and skewness. This paper then answers three questions: firstly, does the combining features which requires more complexity practically improve the results? If yes, how much it can do that. Secondly, which one of the three approaches is the best. And finally which configuration yields the best improvement. The results obtained after experimentations achieved on the Wang database have shown that combining signatures improves surely the results and thus no matter what the manner is considered, the best approach among all tested approaches is the third one of that employs a single formula specifically when considering the Mean-Intersection setting.

Keywords

CBIR; Combining Color Features; Re-ranking Mechanism; Utility Concept

Introduction

The CBIR system aims at selecting, from a repository, a subset of images that satisfy the visual need of the user generally expressed as a query image. Contrary to TBIR which utilizes the annotation, CBIR system employs low level visual features extracted from the images themselves (Rui et al, 1999; Zheng et al, 2010; Smeulders et al, 2000) such as Color, Texture and shape. Each of these descriptors has many signatures. Unfortunately, all the signatures proposed do not return the results as desired by users. One way for improving the quality of the CBIR system is combining signatures. Many works can be found in the literature that falls under the purview of the context of fusion. We can classify them into two classes: the first category is fusion of the textual and visual features such as (Zhiong et al, 2011) in which,

the authors have compared between textual and visual feature from the performance view point, they have concluded that the combination of two information sources can consistently enhance the final accuracy. The second category is fusion visual features such as: (Noureddine Abbadeni, 2009) in which the author has proposed an approach based on multiple representations, multiple queries, and the fusion of results returned by these different representations and queries, (Jian et al, 2010) in which authors attribute weight for each feature based on the relevance feedback, (James et al, 2003) in which, the authors have merged the k first results obtained from four channels; each channel utilizes some CBIR features. There is also third category of fusion of that combining between visual features and audio as in (Manohar et al, 2011). More details in fusion multimodal information can be found in (Guan et al, 2010). We address in this paper the second category. The question to ask here in which step we should combine signatures: during the indexation process or during the matching stage or combining only the results. We experiment here three ways of fusion: the re-ranking considered as fusion in a hierarchical manner, the utility concept consisting of combining only results and proposing not weighted formula that fuses signatures during the matching process. Combining features during the indexation process as used in (Anne et al, 2001) were not performed in our work owing to a multi-dimensional curse which might be generated.

The rest of this paper is arranged as follows: section 2 covers the first fusion manner considered here which is re-ranking. The second manner based on the Utility Concept is discussed in section 3. The section 4 is devoted to the third manner of that combining feature using a single formula. Experiments conducted and tools utilized are presented in section 5 with results discussion. We end this paper by a conclusion which draws some perspectives of this study.

Re-ranking Mechanism via the Relevance Feedback

Re-ranking consists of re-ordering the first images

returned by the system using the user judgment. This mechanism is known as relevance feedback tool. Relevance feedback has been shown to be a very effective tool for enhancing retrieval results in text retrieval. In content-based image retrieval, it is more and more frequently used and very good results have been obtained. In our work, the re-ranking process, which aims to refine results, is done automatically by applying another signature or another similarity measure different to the one that employed during the first ranking. This method has been used in (Jaekyong et al, 2009) when the authors of this paper have used global and local features in hierarchical manner. They have applied the Fuzzy C-Means clustering method firstly using global features as an indexing signature, and then the results obtained have been fined utilizing local features.

Utility Concept

The second method considered is inspired from the utility concept (Fishburn, 1998) which consists in assigning higher scores to relevant images in descending order of their rank within the returned results. The value assigned to each image is given by the following formula:

$$V = \frac{1}{N} * (N - R) \tag{1}$$

Where N: is the number of the returned images and R is the rank of the image. The value V belongs then to the range of 0 to 1. Combining features imposes then to count for each image its total V by summing up its values over all the considered signatures. Based on the new total value, the images have to be ranked and will be visualized to the user.

Combining Signatures in the Same Equation

This third manner consists of fusion signatures during computing similarity. We assign the same weight to all signatures considered. The value of distance or similarity for each signature is normalized before fusion. The distance is normalized by dividing the given distance by the greater distance obtained. For the similarity, we mean here the intersection; it is mapped to normalize distance by the following formula:

$$ND = 1 - \left(\frac{S}{GS}\right) \tag{2}$$

Where ND: is the normalized distance obtained, S: is the similarity value being mapped and GS: is the greater similarity value obtained.

Tools Experiments and Results

In this section, we firstly, present the different methods and tools utilized during the series of experimentation conducted.

1) Indexing Signatures

We point here the different signatures considered in our work.

- *Color Histogram*

A large number of indexing methods for CBIR are reported in the literature, one of which is a color histogram reported in (Swain and Ballard, 1991). This last technique has been employed in many works and is admitted as one of the oldest, yet, basic methods for CBIR. The histogram itself is a statistic vector, the elements of which hold the pixels count for each color in the image.

- *Color Moments*

a) The Mean

$$\grave{u}_i = \frac{1}{N}\sum_{j=1}^{N} f_{ij} \tag{3}$$

b) The Variance

$$\sigma_i = \sqrt{\frac{1}{N}\sum_{j=1}^{N}\left(f_{ij} - \grave{u}_i\right)^2} \tag{4}$$

c) The Skewness

$$\pounds_i = \left(\frac{1}{N}\sum_{j=1}^{M}\left(f_{ij} - \grave{u}_i\right)^3\right)^{1/3} \tag{5}$$

2) Matching Measure

- *Euclidean Distance*

$$l_2(F, F') = \left(\sum_{m=1}^{M}\left(F_m - \grave{F_m}\right)^2\right)^{\frac{1}{2}} \tag{6}$$

Where: F and F' are the vectors being compared.

- *Histogram Intersection*

$$d_\cap(F^q, F^d) = \sum_{j=1}^{n} min(F^q, F^d) \tag{7}$$

Where F^q and F^d are the two histograms to compare and n is the number of bins.

3) Evaluation of Methods under experimentation

For evaluating the performance of the methods, we have used the Precision and Recall measures (Babu et al, 1995). The precision is defined as the ratio of images retrieved to all images retrieved, while the recall is defined as the ratio of relevant images retrieved to all relevant images in a database, or the

probability is given that an image is relevant that it will be retrieved. The both measures are given respectively by the followings formulas:

$$Precision = \frac{Number\,of\,relevant\,images\,retrieved}{Total\,number\,of\,images\,retrieved} \qquad (8)$$

$$Recall = \frac{Number\,of\,relevant\,images\,retrieved}{Total\,number\,of\,relevant\,images\,int\quad he\,Database} \qquad (9)$$

All the methods considered have been tested on the Wang data base posted on line on (http://Wang.ist.psu.edu/docs/related.shtml).

FIG. 1 SOME IMAGES REPRESENTING ALL THE CLASSES OF THE WANG DATABASE

Results and Discussion

Before showing the results of the three fusion manners being compared, we present firstly the results obtained by the primitive signatures without fusion.

TABLE 1 PRECISION VS. RECALL OVER THE PRIMITIVE SIGNATURES CONSIDERED

Recall (%)	Precision (%)			
	Intersection	Mean	Variance	Moments
10	100	100	100	100
20	92.87	79.52	34.28	84.22
30	65.70	72.36	31.65	56.78
40	58.46	70.88	26.72	45.61
50	55.30	58.23	21.68	39.45
60	52.64	52.46	20.99	40.36
70	50.88	41.62	21.02	38.09
80	36.26	42.01	20.25	37.12
90	34.16	33.11	16.26	33.68
100	29.65	30.49	13.84	28.63

Noting that *Moments*: is a vector containing the three low moments: mean, variance and skewness.
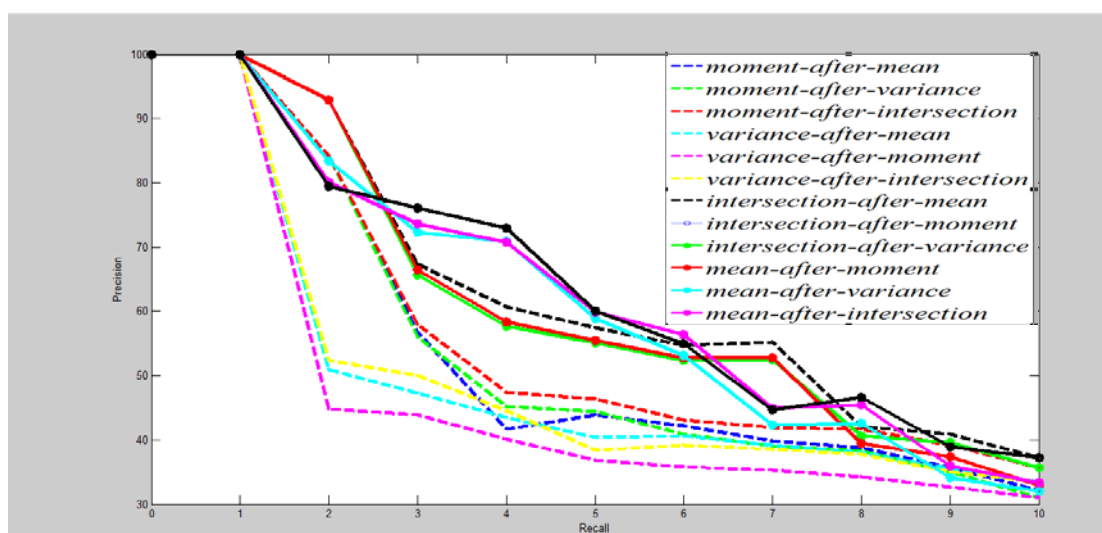

FIG. 2 THE RESULTS RETURNED WITH THE RE-RANKING STRATEGY OVER DIFFERENT COMBINATIONS
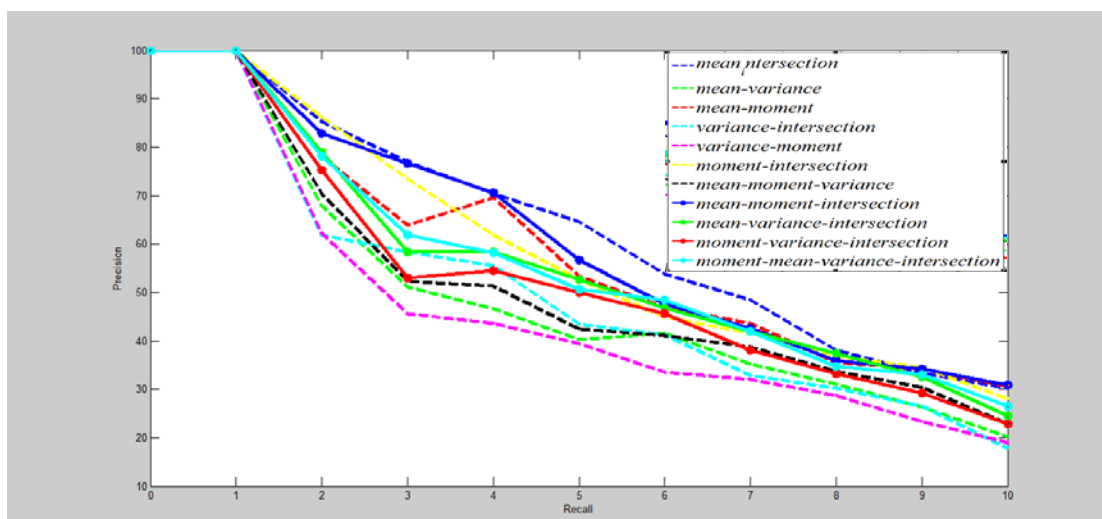

FIG. 3 THE RESULTS RETURNED WITH UTILITY CONCEPT STRATEGY OVER DIFFERENT COMBINATIONS

- The first fusion strategy: Re-ranking

The Fig. 2 presents the results in terms of Precision-Recall obtained with the re-ranking manner.

While the scenarios given in the Fig. 2 are respectively:

Moments_after_mean,   Moments_after_variance, Moments_after_intersection,   Variance_after_mean, Variance_after_moments,   Variance_after_intersection, Intersection_after_mean,   Intersection_after_moments, Intersection_after_variance,   Mean_after_moments, Mean_after_variance, Mean_after_intersection.

The quality obtained with re-ranking can be deteriorated if the second method used within the re-ranking mechanism is worse than the first. Mean_after_intersection and intersection_after_mean are the best, and are even better than the mean and the intersection.

- The second fusion strategy: Utility concept

The Fig. 3 below presents the results in terms of Precision-Recall obtained with the Utility concept manner.

While the scenarios given in the Fig.3 are respectively:

Mean_intersection,   Mean_variance,   Mean_moments, variance_intersection,   variance_moments, moments_intersection,   mean_moments_variance, mean_moments_intersection, mean_variance_intersection, moments_variance_intersection, moments_mean_variance_intersection.

The fusion with this manner can also deteriorate the performance of the primitive method if this one is of high quality with respect to other primitive methods. Among all the combination tried out, we can say that Mean_intersection is the best and it is also better than the mean and the intersection.
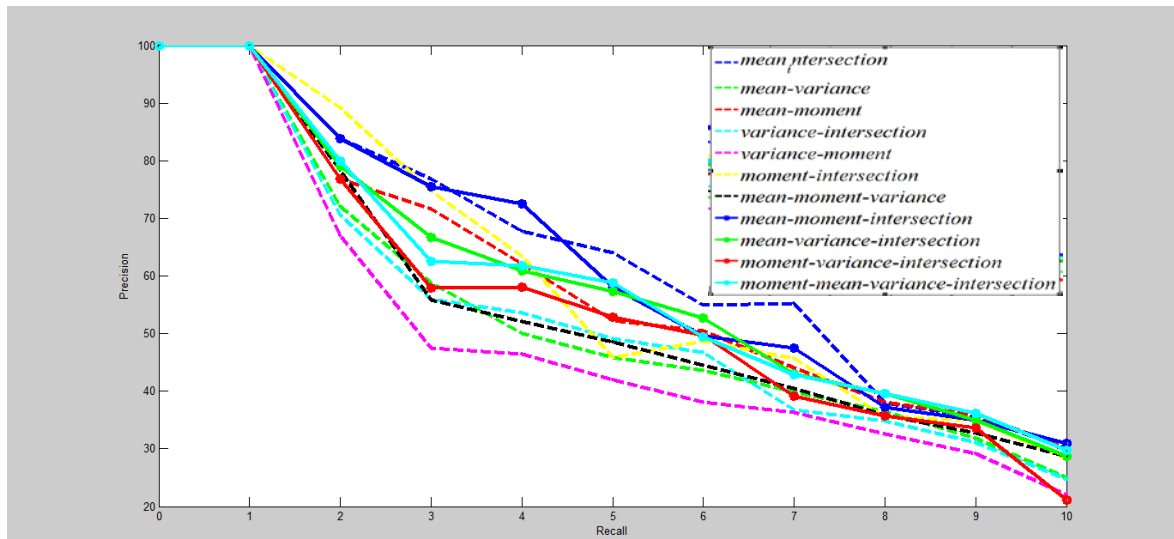

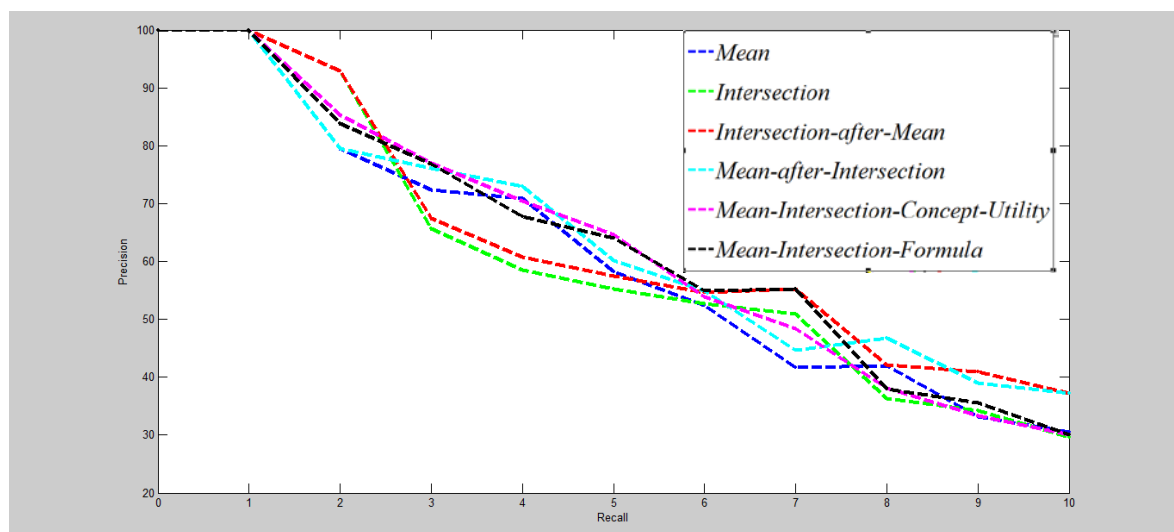FIG. 4 THE RESULTS RETURNED WITH EQUATION STRATEGY OVER DIFFERENT COMBINATIONS

FIG. 5 COMPARISON BETWEEN THE BEST CASES OVER THE THREE FUSION STRATEGY

- The third fusion strategy: Equation

The Fig. 4 presents the results in terms of Precision-Recall obtained with the Utility concept strategy.

While the scenarios given in the Fig. 4 are respectively:

Mean_intersection, mean_variance, mean_moments, variance_intersection, variance_moments, moments_intersection, mean_moments_variance, mean_moments_intersection, mean_variance_intersection, moments_variance_intersection, moments_mean_variance_intersection.

The fusion with this manner can also deteriorate the performance of the primitive method if this one is of high quality with respect to other primitive methods. Among all the combination tried out, we can say that Mean_intersection is the best and it is also better than the mean and the intersection.

- Comparison between the best cases over all fusion strategies

While the scenarios given in the Fig.5 are respectively:

Mean

Intersection

Inter_after_mean: is re-ranking results obtained employing mean signature and so by using Histogram Intersection with 27 fixed bins.

Mean_after_Inter: is re_ranking results obtained employing Histogram Intersection method and so by using the mean signature.

Mean_inter_concept: is combining the both signatures: mean and Histogram using the utility concept fusion manner.

Mean_inetr_formula: is the combination of the both signatures: mean and Histogram using a single formula.

Conclusion

In this paper, we deal with the fusion features considered as a solution for improving results returned by a CBIR system. Three statistic strategies have been experimented: the re-ranking, Utility Concept and a single equation. Based on the results found, we claim that combining features using a single formula is the best way. For obtaining better results, the signatures combined should be of high quality. We do not assign any weight in our formula, considering weighting can also be effective.

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